Implementation of Genetic Algorithm as the Part of Dicrete Simulation in Production Planning

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***Abstract*— The survival and growth of businesses in today's market is based on constant innovation and new product development. Business innovation must take place at all levels, from products, processes to the organization itself, in order to bring about improvements in competitiveness and business efficiency. Furthermore, the number of different components of many products, and, consequently, the demands for the appropriate manufacturing processes and operations, have also increased manifold. We can respond to such demands and manage the appropriate tools to simulate the activities and processes within the factory in the virtual world. The simulation of the entire flow of materials, including all significant activities of production, storage and transportation are key requirements for quality production planning and the necessary manufacturing processes. Discrete simulations, i.e. the applications used for running this type of simulation provide the possibility of creating different scenarios concerning cases of different production parameters, the burden of production capacities, as well as their delays and failures. A further step in the development of the simulation model is the creation of a genetic algorithm for the purpose of minimizing costs and delivery times of products.**

Keywords: process planning, production planning, discrete simulation, genetic algorithm

I. Introduction

Faster innovation processes and increase in number of new products developed and sucesfully placed on the market presents a great challenge for most companies. The main reason is their traditionally serial, distributed, manual guidance of the process wherby the most frequent product is unnecessary paperwork. The result of this kind of business is slow NPDI, expensive and inflexible processes which whitout visualization become difficult to manage and controll.

The solution to this problem is shown in the form of creating digital production as a tool of PLM (Product Lifecycle Management) business approach. Thanks to its capability to link all information about products and processes of the organization, PLM systems can significantly reduce the activity that adds no value and create a foundation for the collaboration of all departments within the organization in real time using all the necessary information about the product throughout its lifecycle [1].

II. PLM as a Production Strategy

As an effective solution for connecting human resources, business processes and systems, product information and services is new business approach called PLM (Product lifecycle management). This approach enables collaborative creation, management, expansion and use of product information throughout the enterprise from initial concept to product disposal [1].

PLM is defined as a strategic business approach for effective management and use of corporate intellectual assets. PLM systems meet the need of connecting all the resources and information that arise during the lifecycle of the product [2].

PLM is a business approach that uses a different business solutions to connect, create, manage, distribute and use the product information throughout the enterprise [3]. This solution supports integration of people, processses, business systems, tools, methods, technologies and data.

One of the tools of PLM systems are simulations and creation of digital production which is faster and cheaper way to plan production process. With the simulation of production and generation of all processes, digital production offers the possibility for optimization of the existing system. It is very difficult to mathematically describe complex processes, and for their execution is required large amount of funds, because of that solutions such as operations research methods are used less [4]. In such an environment simulation technology is becoming an increasingly important tool for the analysis of real processes. Below is presented a particular case for which is developed a simulation as part of this project.

III. CASE STUDY

Created simulation model is made in Plant Simulation, part of Siemens PLM Software that enables the creation of discrete simulation. The simulation model is designed for an virtual company that has a predefined production for a certain period. So, the company has orders from customers who expect the company to meet its obligations within certain time limits. Setting the time limits is necessary in order to calculate the required capacity of resources which are also the available resources of the company. Within this model, defined time limit of production is a period of one year.

Arriving to the company customer orders become warranties which contain information about the type of product, quantity, number of series, order date and time of delivery. Also for creating a simulation it is necessary to dispose with information about the technological processes of each product, processing times and set-up times. After completion of capacitive sizing and programming of all the necessary methods of material flow, initial model was created and among others the results of the availability of production resources were obtained while working in two shifts (Figure 1, 2).

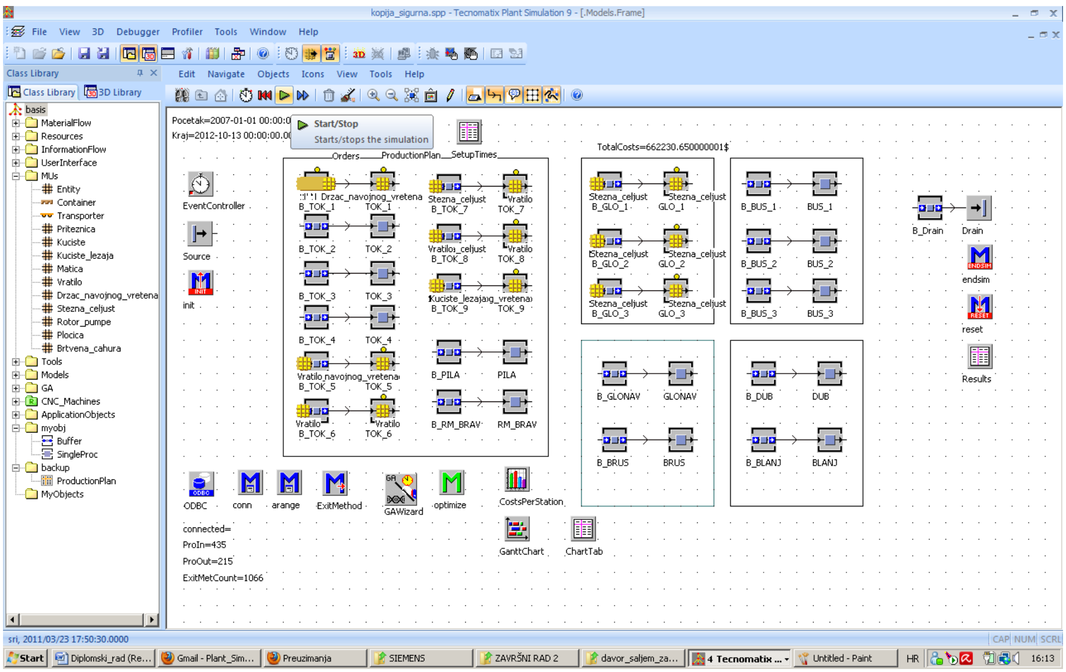

Figure 1. Initial created model in Plant Simulation

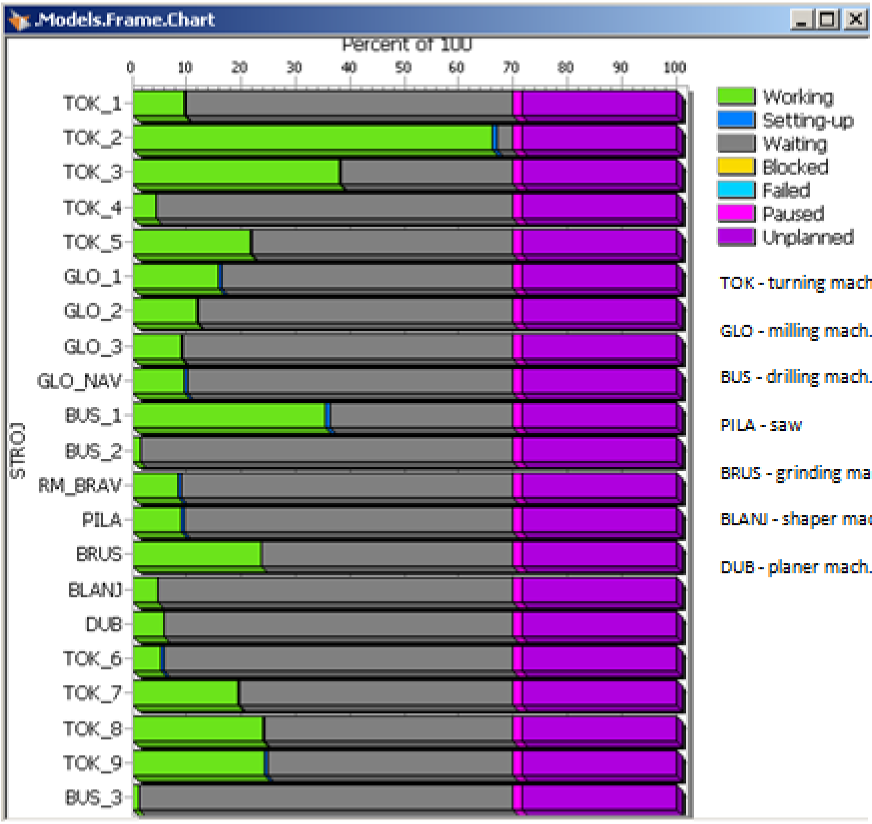

Figure 2. The availability of machines in initial model working in two shifts

"Fig. 2," shows improvement in disposition of machine load comparing to the model without capacitive sizing, but some machines still remain much less used.

In this model each product unit for completing one type of operation have on disposition not one but all machines on which this certain type of operation can be performed. Of course, if we define a machine as CNC, machining center or classic, the choice of the machine will affect the totall cost and the total time of producing all product series.

Since the profit per product is in direct correlation with the cost of making products selection of the best variant is of great importance.

For creation of genetic algorithm in the simulation model was used Genetic Algorithm tool. Some parameters are defined through the method genetic algorithm, and some are defined in the genetic algorithm Wizard.

To use a genetic algorithm, it is necessary to define the objective function and constraints. For this model the objective function is more complex. Specifically the aim is to produce all the products with the minimum cost, but also with the requirement to comply with the delivery date. Therefore, the algorithm is defined by a total of eleven objective functions. One of them is a requirement for the lowest cost of all products together, and the other ten are related to a request for minimum production time of each product series. Because there are several objective functions it is necessary to determine their weight or prioritie factors. They are determined subjectively where for each function can be assigned value from 0 to 1

Due to the specific input of constraints we created a new variable *Series* which measures the number of products in the series. The constraint in the algorithm represents the number of machines that are available for particular product to execute particular operation are. So each product has a number of constraints in accordance with following expressions (1):

$$(P1\ x\ K1_1\ x\ MK1_1\ x\ KP1) + (P1\ x\ K2_1\ x\ MK2_1\ x\ KP1) + \dots + (P1\ x\ Km_1\ x\ MKm_1\ x\ KP2)$$
for product $P1$

$$(P2\ x\ K1_2\ x\ MK1_2\ x\ KP2) + (P2\ x\ K2_2\ x\ MK2_2\ x\ KP2) + \dots + (P2\ x\ Km_2\ x\ MKm_2\ x\ KP2)$$
for product $P2$ (1)

$$(Pn\ x\ K1_n\ x\ MK1_n\ x\ KPn) + (Pn\ x\ K2_n\ x\ MK2_n\ x\ KP2) + \dots + (Pn\ x\ Km_n\ x\ MKm_n\ x\ KPn)$$
for product Pn

Where :

P_n = type of product (numerical value 1)
Km_n = m-th type of operation for n-th type of product (numerical value 1)
MKm_n = number of possible machines for making m-th type of operation for n-th type of product
KP_n = quantity of product,

With this a form of particular constraint can be defined, as in (2):

$$MKm_{n\text{-}min} > P_n\ x\ Km_n\ x\ MKm_n < MKm_{n\text{-}max} \tag{2}$$

With the constraints and objective function there also must be defined size and number of generations and number of observations per individual. Generation represents a number of solutions that the algorithm combines, and observation represents a number of simulations for each new generated individual [5]. Thus the total number of simulations are calculated by (3):

$$\text{Size of generation x (2 x Number of generations - 1) x Observations per individual.} \tag{3}$$

In this model following parameters are set:

Size of generation = 25
Number of generations = 12
Observations per individual = 2

Here by is defined genetic algorithm, and the results are shown in the following section.

I. Results Analysis

With the same working conditions (working hour cost, machine availability, processing time per part) developed genetic algorithm demonstrated very good results and in correlation with unoptimized model. Total processing time for all products in one year production has been reduced by 28 days and the reduction of production cost was in total 18000 dollars (Figure 3).

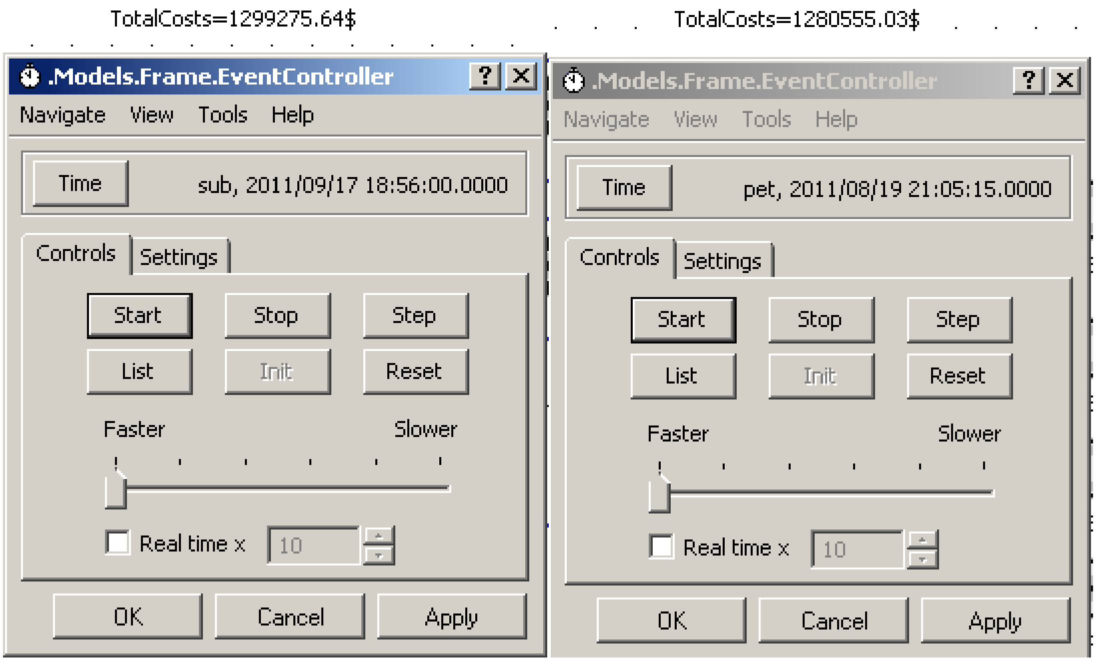

Figure 3. Result comparison of two developed simulation models

Total savings in money is even more since optimized model finishes almost one month earlier with production, and in real continuous systems new processes could start earlier bringing new profit per product. Because of this total costs of optimized system should be diminished for a money value that system is able to produce in time of 28 days. With this cost of production for optimized model are reduced and profit per product is increased.

“Fig. 4,” showes how numerical value that describes quality of obtained solution changed per generation.

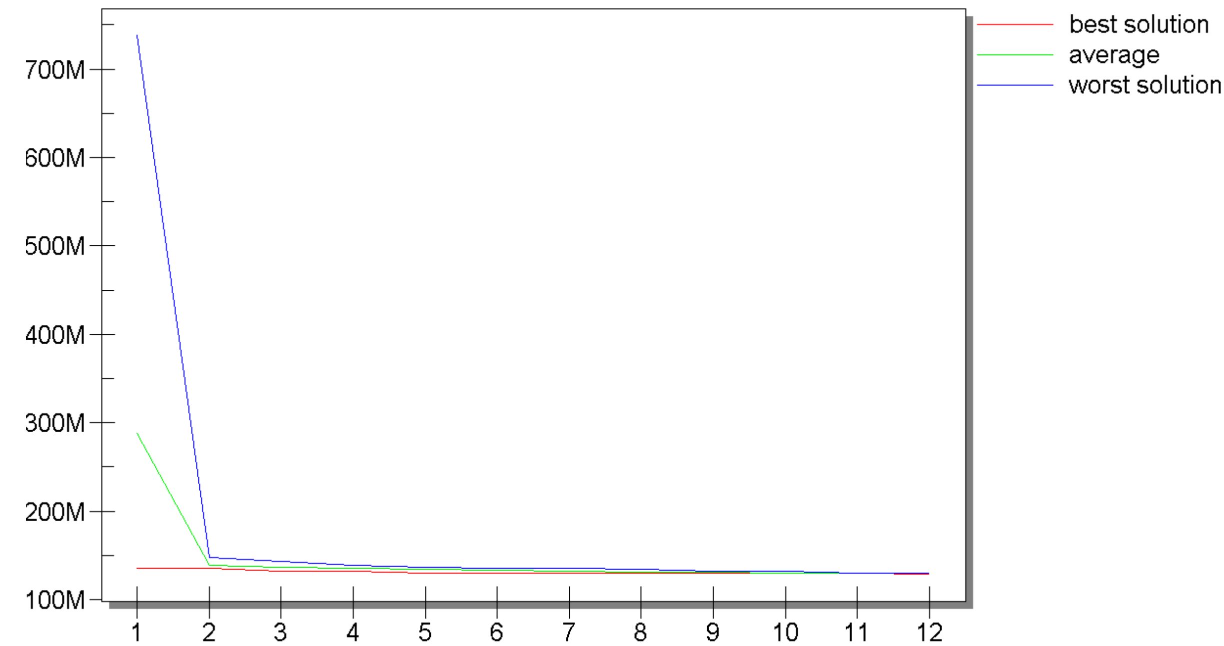

Figure 4. The change of fitness function value through 12 generations

Results of simulations deviated from optimal result through first three generations. With the increased number of generations the quality of results had also improved.

Genetic algorithm in total generates 570 individuals through 12 generations, and with 2 obsservations per individual runs in total 1140 simulations. The best individual is generated in last (12th) generation and first obsservation. It's, and also best fitness function of all simulations is 128755698.521.

"Fig. 5," shows the structure of total costs per machine in optimized model.

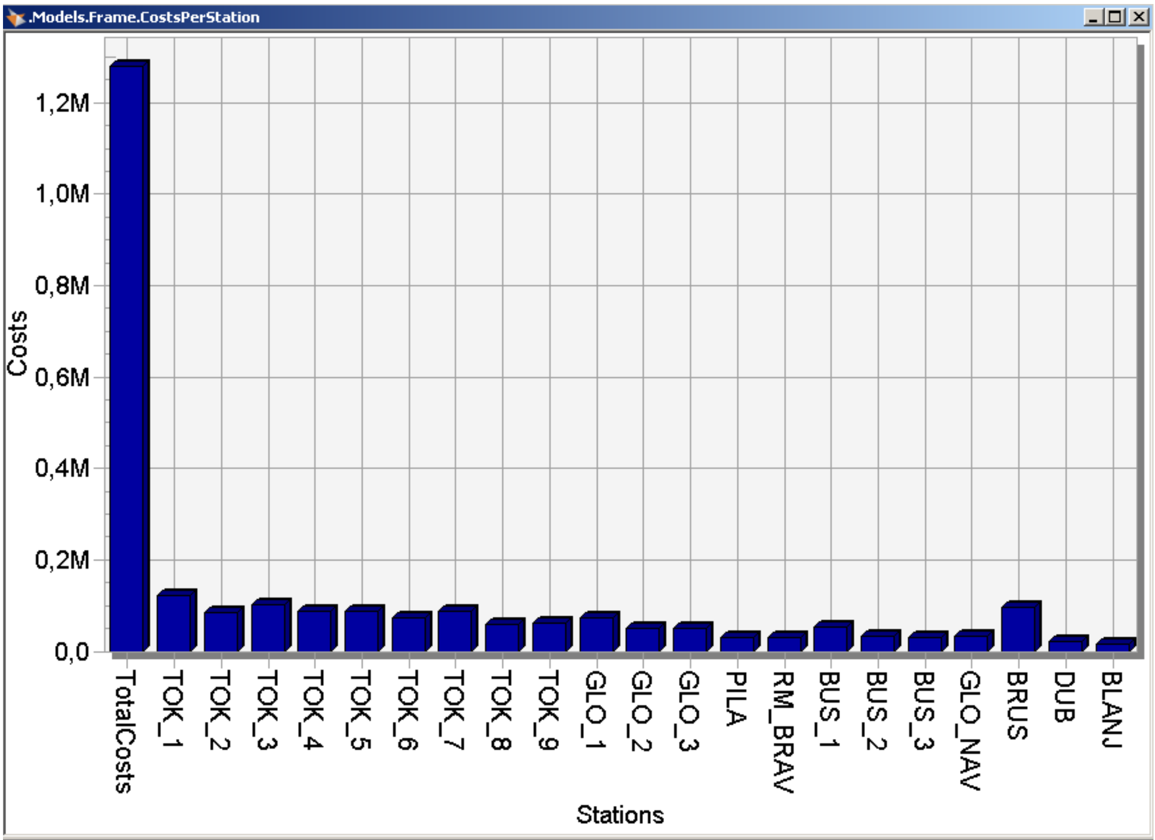

Figure 5. Structure of costs

CONCLUSION

This project showed the idea of using simulations as a tool for production planning that allows user to optimize the results of existing systems. Although simulation model has been made for possible scenario of production all input values are obtained from real observed processes and so the model is usable in real production systems. Simulation displayed differnet behavior of system according to variable production data (as variations of machines, different cost production per machine, different availability of machines, variable delivery times and working shifts). Also visualization helped identifing, understanding and conecting new informations with constant changes inside manufacturing processes of one organization. Creating SQL database for crated model and connecting it with internet technologies increased flow rate of informations. As a most important task to optimize system a genetic algorithm was developed and it showed very good results and improvement in production system regarding production costs. Comparing to nonoptimized model production cost were reduced 3% of annual turnover and production time for all products in in one year was 28 days less. Project achieved all conditions for further evaluation in real environment.

REFERENCES

[1] A. Saaksvuori, "Product Lifecycle Management", Springer-Verlag, 2008.
[2] J. Stark, "PLM: 21st century Paradigm for Product Realisation", Springer-Verlag, 2004.
[3] J.Teresko, "The PLM Revolution", IndustryWeek, 2004.
[4] S. Bangsow, "Manufacturing Simulation with Plant Simulation and SimTalk", Springer, 2010.
[5] Tecnomatix Siemens, "Tecnomatix Plant Simulation 9 User Guide 2008", 2008.